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Advancements in Poultry Disease Detection: A Comprehensive Review of Deep Learning Methods and Emerging Trends

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Abstract: For a long time, farmers in this society have relied on specialists to identify and diagnose illnesses in chickens. Consequently, due to inadequate expertise or delayed diagnosis, farmers lose a great deal of domesticated birds. By utilizing computer vision and image analysis techniques, artificial intelligence and machine learning tools make it possible to quickly identify the most prevalent diseases afflicting chickens from pictures of their droppings. In this work, we suggest a deep learning method based on Convolution Neural Networks (CNN) to determine whether chicken excrement falls into one of the three categories. We address the same issue and create a solution by utilizing pre-trained models.

Poultry productivity and profitability are seriously threatened by illnesses, despite the fact that poultry farming is crucial to both global food security and economic growth. Farmers suffer significant losses as a result of traditional diagnostic techniques, which frequently lead to late detections or reliance on limited expertise. Promising solutions for early and accurate disease identification in chickens can be achieved by utilizing machine learning (ML) and artificial intelligence (AI) techniques, specifically computer vision and deep learning (DL). In this work, we present a thorough method for categorizing chicken diseases from Utilizing convolutional neural networks for fecal images (CNNs). We compare the effectiveness of many pre-trained models, showing that the XceptionNet model achieves a validation accuracy of 94%, outperforming the others. Furthermore, we utilize the Inception-V3 method for data imbalance problems and oversampling strategies.

Keywords: Convolution Neural Networks, computer vision, deep learning, XceptionNet, Inception-V3

INTRODUCTION

As the world's largest supplier of protein to an expanding population, the poultry sector is critical to both economic growth and global food security. The business does, however, have serious difficulties because of the periodic outbreaks of diseases including Newcastle disease, salmonellosis, and avian influenza. These epidemics represent major health risks to people in addition to causing farmers to suffer significant financial losses. Conventional disease detection techniques, which depend on manual observation, are frequently labor-intensive, time-consuming, and unreliable, which causes detection to be delayed and preventive actions to be insufficient.

Emerging technologies like computer vision, machine learning, and data mining provide viable answers to these problems in terms of early illness identification and monitoring in poultry. Researchers can spot trends by using automated methods and a lot of data.

Currently, manual observation is the main method used to detect diseases in poultry. This method can be labor-intensive, time-consuming, and unreliable, and it may not identify sick birds in a timely manner. promising new technologies in the field of poultry disease monitoring and detection include machine learning and data mining. Large amounts of data can be processed to find patterns and relationships between variables with the aid of automated methods. Finding patterns and classifying arrays in databases is one area in which machine learning algorithms thrive. Digital image processing and machine In recent years, learning methodologies have garnered more attention, especially when it comes to the welfare of chickens. Scholars have employed diverse methodologies, including as

Deep learning technology can be used to categorize diseases that affect hens, a new technological advance made feasible by the availability of vast amounts of data. Large volumes of data are readily available, allowing for the provision of different types of data in varied quantities.

But in a classification, there are typically some class members with a different number. An uneven class distribution results in a class imbalance distribution of the data and a smaller number of members of the minority class than of the dominant class (Ustyannie & Suprapto, 2020). Due to this circumstance, the categorization procedure is incorrect and favors the dominant class over the minority class (Kaope & Pristyanto, 2023).

LITERATURE REVIEW

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Methodologies

1. Deep learning is being used in this study to detect diseases in chickens. After YOLOv3 separates droppings from photos, a pre-trained ResNet50 model determines if the droppings are healthy or indicative of NewCastle Disease, Salmonella, or coccidiosis.
2. This study suggests a method for diagnosing illnesses in chickens by utilizing smartphone photos of the droppings of the birds. The system makes use of two deep learning models: ResNet50 identifies the droppings as either healthy or containing one of three diseases (NewCastle Disease, Salmonella, or Coccidiosis) once ResNet3 has isolated the droppings from the image.
3. Using fecal pictures, a deep learning method is suggested for the classification of illnesses in chickens. The process includes configuring the project environment, compiling and preparing a dataset, and writing and testing Jupyter notebook code for handling data and training/evaluating models. For these phases, reusable components are developed, and then a training pipeline is constructed to automate the training of the model. The performance of the trained model is then assessed. The model can optionally be deployed as a web application, packaged using Docker, and a continuous integration/continuous deployment pipeline can be implemented as part of the project extension.
4. AI virus detection uses an etiological methodology that includes isolation of viruses from chicken embryos, RT-PCR for subtype identification, and serological methods such as HI tests and ELISA for antibody detection. Viral RNA can be detected sensitively using molecular techniques like real-time RT-PCR, however onsite implementation issues require investigating new strategies.
5. The method uses AI and deep learning, particularly CNNs, for automated health surveillance and early anomaly identification in order to manage poultry diseases. It looks into non-invasive diagnostic methods, solves technological problems like data scarcity and cost-benefit analysis, and integrates computer vision with animal care.
6. For the purpose of early disease identification in poultry, the methodology integrates deep learning models, infrared thermography (IRT), and behavioral analytic techniques. It leverages machine learning algorithms to enhance physiological factors like body temperature, vocalization patterns, and fecal features.
7. For the purpose of classifying images of chicken excrement, this work uses InceptionV3, preprocessing methods, and oversampling to balance the data. Accuracy, recall, precision, and the computation of the F1-Score using a confusion matrix are all included in the model evaluation.
8. Using methods like transfer learning, the study applies CNNs, such as Inception, DenseNet, and MobileNet architectures, for predicting chicken disease from fecal photos. After data gathering, 6812 preprocessed and enhanced photos from chicken farms are obtained. Inception V3, DenseNet-121, and MobileNet architectures—each with unique parameter settings—are used to train and assess the models.
9. Both custom CNN architecture and pre-trained XceptionNet, an optimized architecture with depth-wise separable convolutions that provides efficient classification for chicken disease detection, are used in this study. The first is a custom CNN architecture that was designed from scratch and uses stacking convolution layers with ReLU activation and softmax output for multi-class classification.
10. YOLO-V3 was utilized in the study to precisely segment the region of interest (ROI) from photos of chicken feces. A pre-trained ResNet50 model was then used to accurately classify the diseases. In order to rectify the class imbalance, oversampling and data augmentation approaches were applied, guaranteeing strong model training and performance.
11. For accurate chicken disease identification and classification, Utilizing convolutional neural networks (CNNs) like VGG16, ResNet50, and MobileNet, the study applies transfer learning. Data augmentation techniques are used to increase the diversity of the dataset, and experiments are conducted to assess the model's performance with various numbers of epochs.

Technologies

1. This technique recognizes diseases using deep learning.. The object detection algorithm YOLOv3 locates and separates the chicken droppings in the picture. The droppings are then analyzed by a pre-trained ResNet50 image classification model, which determines whether they are healthy or indicative of Salmonella, Coccidiosis, or NewCastle Disease. Researchers employed geometric adjustments to enhance data variety and oversampling for underrepresented classes to improve training data.
2. The following technologies are used to detect and classify poultry diseases: object detection algorithms, image classification algorithms, deep learning, YOLO-V3 object detection algorithm, ResNet50 image classification model, and convolutional neural networks (CNNs).
3. The document mentions using TensorFlow library for deep learning and Docker for deployment purposes.Oversampling for underrepresented classes and geometric adjustments to enhance data diversity were employed by the researchers to improve the training set.

4. Innovative technologies like portable impedance biosensors and immunomagnetic beads coupled with nanotechnologies offer rapid subtyping and quantitation of AI viruses. These advancements cater to diverse scenarios in the poultry supply chain, emphasizing on site usability and ultrasensitive detection capabilitiesOversampling for underrepresented classes and geometric adjustments to enhance data diversity were employed by the researchers to improve the training set.
5. The study utilizes fluorescence immunochromatographic test (FICT) for detecting H5 HPAIVs, surpassing traditional methods like colloidal gold-based RDTs. It also employs sandwich FLISA and western blot analysis for antigen detection and characterization of antibodies, alongside immunofluorescence assay (IFA) and lateral flow test strips for rapid and sensitive H5 influenza virus detection.Underrepresented class oversampling and geometric adjustments were employed by the researchers to enrich the training data and add more variation to the data.
6. The technologies used are infrared thermography to detect changes in body surface temperature, deep learning models to classify chicken feces and identify abnormal vocalizations, and deep convolutional networks to identify aberrant behaviors suggestive of illness in behavioral analysis.Researchers employed geometric alterations to boost data variety and oversampling for underrepresented classes to improve training data.
7. This study utilizes InceptionV3 CNN model with oversampling in data processing for classifying chicken manure images. Data preprocessing involves oversampling to balance the dataset, resizing to 229x229 pixels, and augmentation techniques. Evaluation is done using confusion matrix-based metrics: accuracy, recall, precision, and F1-Score. Underrepresented class oversampling and geometric adjustments were employed by the researchers to enrich the training data and add more variation to the data.
8. The study employs supervised learning with CNN for chicken poop classification into Healthy, Coccidiosis, Salmonella, or Newcastle categories. Data collection yields 6812 images, and preprocessing involves balancing, resizing, and augmentation. Three CNN architectures (InceptionV3, DenseNet-121, MobileNet) are utilized, trained, and evaluated for disease detection, enhancing diagnostic accuracy. Researchers employed geometric alterations to boost data variety and oversampling for underrepresented classes to improve training data.
9. The setup uses Kaggle Environment with TPU-v3:8, Python v3:7 on a 16 GB RAM computer. 1590 fecal images from Kilimanjaro and Arusha regions, distributed across three labels, are collected. It employs custom CNN and pre-trained models (VGG, ResNet, XceptionNet, MobileNet) for chicken disease detection.Researchers employed geometric adjustments to enhance data variety and oversampling for underrepresented classes to improve training data.
10. The system was developed using Darknet for YOLO-V3 implementation, Python with Django framework for backend API development, and Flutter for creating a mobile application interface. Models were converted to TensorFlow Lite format for efficient deployment on mobile devices.Researchers employed geometric adjustments to enhance data variety and oversampling for underrepresented classes to improve training data..
11. The study utilizes Convolutional Neural Networks (CNNs) such as VGG16, ResNet50, and MobileNet for image processing and classification. Data augmentation techniques are applied using tools like Roboflow to increase the dataset size and diversity.Oversampling for underrepresented classes and geometric adjustments to enhance data diversity were employed by the researchers to improve the training set.

Best Practices

1. Though the technique gives some indications, the text doesn't go into detail on specific recommended practices. Improved model generalizability and possibly corrected class imbalance were achieved through oversampling and geometric manipulations of the data. Selecting a pre-trained ResNet50 model also implies using an established method for picture classification.
2. This study ensured accurate identification of chicken disease by adhering to strict procedures throughout, from data collection to model training and evaluation. The models were successfully trained by using preprocessing approaches and a variety of datasets. Results were encouraging when carefully chosen neural network designs were combined with transfer learning. Thorough assessment metrics offered insightful information. All things considered, following best practices made it easier to create trustworthy models for the early diagnosis of diseases affecting chickens.
3. The project makes use of industry best practices, such as modular components for maintainability, explicit coding structure with comments and descriptive names, and version control with Git. For dependability, it also makes use of configuration files and maybe unit testing.
4. The study pushes for the use of cutting-edge methods by highlighting the significance of application-oriented development in AI virus detection throughout the chicken supply chain. It

emphasizes the necessity of both technological monitoring and legislative actions for successful prevention, with vertical integration providing encouraging opportunities to improve biosecurity.

5. The use of cutting-edge diagnostic techniques like FICT, FLISA, and IFA, the integration of AI and deep learning for automated health surveillance, and the resolution of technological issues like data scarcity and cost-benefit analysis in poultry disease management are examples of best practices.
6. To improve production outcomes and animal welfare through proactive intervention, deep learning models, infrared thermography, and behavioral analytic approaches are integrated in best practices for automated disease diagnosis in chicken farming.
7. Using oversampling to prioritize data balancing guarantees class equilibrium for accuracy. The quality of datasets is improved by standardizing image sizes and using augmentation techniques. Robust performance assessment is ensured by utilizing architectures like InceptionV3 CNN and assessing using metrics like accuracy and recall.
8. To ensure representativeness, a diverse collection of chicken feces photographs from various sources must be gathered. Preprocessing operations that improve model generalization include data augmentation, resizing, and balancing. Effective disease detection requires the selection of optimal models, such as InceptionV3, DenseNet-121, or MobileNet, depending on efficiency and performance parameters.
9. After setting up Kaggle Environment using TPU-v3:8, we gathered a variety of fecal photos from Arusha and Kilimanjaro. We optimized models for the detection of chicken disease using both transfer learning and CNN created from scratch. In order to improve poultry illness diagnostics, we balanced computational efficiency and accuracy by utilizing architectures such as VGG, ResNet, XceptionNet, and MobileNet.
10. To improve the system's classification skills, the study made use of transfer learning with ResNet50, a tried-and-true method for feature extraction in deep learning models. To balance class distribution and lessen classification bias, random oversampling (ROS) was used.
11. The study uses transfer learning, which reduces the requirement for a large amount of labeled data by using pre-trained models to facilitate effective learning on a customized dataset. In order to improve model generalization and mitigate overfitting, data augmentation is utilized to increase dataset diversity.

Challenges

1. This study tackles shortcomings in previous deep learning algorithms (restricted illness scope and lack of data for uncommon diseases) as well as limitations in traditional methods (error-prone observations and impractical lab testing).
2. Conventional techniques for detecting diseases in chickens are prone to mistakes andnot appropriate for continuous use. Furthermore, there are limitations with existing deep learning techniques: they might not be able to identify specific diseases and might be impacted by the innate structure of chickens, and may have been trained on erroneous data that included irrelevant background items.
3. Obtaining a sizable, accurately labeled dataset of chicken fecal photos and managing image quality variables like lighting or magnification are frequent obstacles in this sector. Another problem is making sure the model can adjust to data that hasn't been seen yet.
4. The adoption of traditional techniques for poultry surveillance on-site presents obstacles, which has led to the investigation of new alternatives. The continuous difficulties in AI virus surveillance are highlighted by the requirement for quick and accurate detection techniques that may be used in a variety of contexts throughout the chicken supply chain.
5. Addressing data quality, bias, and diversity concerns is a challenge in picture classification, particularly When working with datasets that exhibit unequal distributions of classes. It is critical to overcome computational constraints in order to train big models and optimize performance on edge devices. Maintaining the stability and comprehensibility of deep learning models to thwart hostile assaults and bolster credibility is still a top concern.
6. Managing technological obstacles including data scarcity and cost-benefit analysis when applying AI and deep learning technologies are challenges in the control of poultry diseases. Furthermore, there are obstacles in clinical and veterinary contexts related to guaranteeing the scalability and efficacy of innovative diagnostic techniques like FICT and FLISA.
7. Data quality, bias, and diversity concerns are prevalent in picture categorization, especially when dealing with imbalanced datasets. Resource limitations must be overcome in order to optimize edge devices and conduct extensive model training. Robustness and interpretability of deep learning models to fend off adversarial attacks and improve real-world trust are still difficult problems to solve.
8. Dealing with data shortages and quality issues is a challenge, in particular when it comes to datasets from medical imaging that are used to identify chicken disease. Optimizing deep learning models for precise and effective deployment on mobile devices is another significant issue. A major challenge is still making sure these models are reliable and applicable to a variety of agricultural settings and chicken breeds.

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9. The intricacy of multi-class classification for precise illness detection, improving CNN architectures for mobile deployment, and data inconsistency resulting from diverse picture sources are among the challenges.
10. Three major obstacles were solved during the research: addressing class imbalance in the dataset, improving models for use with mobile devices, and striking a compromise between computing efficiency and accuracy.
11. The monitoring of poultry poses several challenges, such as inadequate lighting, occlusion, and the requirement for extensive and varied datasets. Accurate monitoring is further made more difficult by the requirement to identify individual chickens in highly stocked flocks and to separate birds from the background.

Emerging Trends

1. Classifying diseases in chicken using deep learning is in keeping with a potential trend where deep learning techniques are applied to a range of farming jobs. This might completely change agriculture in a number of ways, including disease detection and crop yield forecasting.
2. The publication notes that academics are able to take on challenging issues like illness identification in poultry because of recent developments in deep learning and the availability of massive datasets. This points to a trend of using deep learning methods in a variety of agricultural applications.
3. Researchers are investigating how to take pictures of chicken excrement with cellphones in order to classify diseases. By doing away with the need to send samples to a lab, this may make it simpler for chicken farmers to identify illnesses in their flocks.
4. New developments in AI virus detection center on the creation of sensitive and quick solutions for on-site use in the chicken sector. Methods that make use of portable biosensors and nanotechnologies are becoming more popular because they can quickly perform subtyping and quantitation, meeting the changing requirements of poultry monitoring.
5. Using AI and deep learning for automated health surveillance and early anomaly detection is at the forefront of emerging trends in the treatment of poultry diseases. Because of their ability to identify changes quickly and sensitively, novel diagnostic techniques like FICT, FLISA, and IFA are becoming more and more popular as a means of meeting the changing demands of the poultry business.
6. In order to revolutionize poultry farming operations, emerging developments center on AI-driven monitoring systems for real-time surveillance of chicken health. These technologies allow for automated illness diagnosis and preemptive intervention.
7. Advanced CNN architectures such as EfficientNet and ViT are being used in image classification in emerging trends to achieve better performance. Model generalization is improved by leveraging transfer learning from large-scale pre-trained models and self-supervised learning. In image analysis, the integration of transformer-based architectures with attention processes improves feature extraction and context understanding.
8. Using cutting-edge AI methods to improve model efficiency and accuracy, such as data augmentation and transfer learning, is one of the emerging trends. Furthermore, there's an increasing focus on creating specialized neural network topologies for certain applications, including agricultural disease detection. Furthermore, the trend toward implementing AI solutions on resource-constrained devices for real-time field applications is reflected in the use of mobile-friendly models like MobileNet.
9. Utilizing various architectures like XceptionNet for increased accuracy, incorporating CNNs for quick poultry disease detection, particularly in resource-constrained contexts, and applying transfer learning for fast model training are some emerging themes.
10. The study demonstrated how deep learning and computer vision may be used to automatically detect diseases in livestock, in line with current trends. This shows how these technologies can be used for in-the-moment monitoring and decision-making in agricultural contexts.
11. The use of convolutional neural networks (CNNs) and deep learning for poultry health monitoring is one of the study's emerging themes. The use of transfer learning to leverage pre-trained models in domain-specific applications is growing in popularity, and data augmentation approaches are improving the performance of models and the diversity of datasets.

Research Gaps

1. While effective, this system can only detect three diseases. Further research is needed to include a wider range. Additionally, data collection for these less common diseases is crucial for a more comprehensive system.Underrepresented class oversampling and geometric adjustments were employed by the researchers to enrich the training data and add more variation to the data.
2. Although this research provides a solution, it can still be improved. Only three diseases can be identified by the system; a larger range has to be investigated in future studies. Furthermore, in order to create a more complete system, data collecting for these uncommon disorders is essential.
3. This deep learning project leverages best practices for code organization and maintainability.

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Practices include using version control (Git), clear and descriptive variable names, comments within code, and modular components. Additionally, configuration files and potentially unit tests are used to ensure project reliability. Researchers employed geometric adjustments to enhance data variety and oversampling for underrepresented classes to improve training data.

4. Research gaps may exist in understanding the long-term performance and scalability of AI-driven monitoring systems in diverse poultry farming environments, highlighting the need for further investigation and validation.
5. Research gaps may exist in understanding the scalability and real-world application of AI and deep learning technologies in poultry disease management. Further research is needed to evaluate the feasibility and performance of novel diagnostic methodologies like FICT, FLISA, and IFA in diverse poultry production systems.
6. Research gaps may exist in understanding the long-term performance and scalability of AI-driven monitoring systems in diverse poultry farming environments, highlighting the need for further investigation and validation.
7. Despite advancements, research gaps exist in addressing challenges such as poor lighting conditions and occlusion in poultry monitoring. Further research is needed to optimize illness detection algorithms, enhance dataset diversity, and develop expert systems for early detection and warning in poultry.
8. Previous works primarily focused on broader abnormality detection in poultry without direct disease identification and segmentation. This research addresses this gap by providing a targeted approach to poultry disease detection, enhancing the specificity and utility of the system for practical farm applications.
9. Research gaps include the need for extensive and diverse datasets representing chicken breeds and environmental conditions. Further investigation into optimal architecture and hyperparameter tuning for deep learning models in chicken disease detection is necessary. Exploring integration of emerging technologies like edge computing and federated learning for decentralized model training in remote poultry farming areas shows promise for future research.
10. This research offers a solution, but there's still room for improvement. The system can only detect three diseases, and further research is needed to include a wider range. Additionally, data collection for these less common diseases is crucial for a more comprehensive system.Researchers employed geometric alterations to boost data variety and oversampling for underrepresented classes to improve training data.
11. Research gaps include improving model interpretability in image classification, enhancing generalization across diverse datasets, and integrating domain knowledge for accurate chicken disease detection.

RECOMMENDATIONS

To propel the field of poultry disease detection forward, it's crucial to expand the range of diseases detectable and improve the robustness of deep learning models. This involves collecting diverse datasets, employing data augmentation techniques, and optimizing model architectures. Additionally, enhancing model interpretability and focusing on practical implementation, such as deploying models on mobile devices, will increase their usability in real-world poultry farming settings. Continuous training for stakeholders and adherence to best practices ensure the long-term effectiveness of these technologies. By addressing these recommendations, researchers can significantly contribute to the advancement of poultry disease detection and management through deep learning.

CONCLUSION

Deep learning technology can be used to categorize diseases that affect hens, a new technological advance made feasible by the availability of vast amounts of data.There is easy access to large volumes of data, which makes it possible to provide various types of data in different quantities. But in a classification, there are typically some class members with a different number.When data are distributed unevenly and the minority class has fewer members than the dominant class, this is known as a class imbalance (Ustyannie & Suprapto, 2020). Due to this circumstance, the categorization procedure is incorrect and favors the dominant class over the minority class (Kaope & Pristyanto, 2023).

FUTURE SCOPE

The literature review on the classification of diseases in domestic chicken offers important new information on how deep learning technology can be used to identify diseases in poultry early and accurately.Using computer vision and machine learning, researchers have developed sophisticated models that can reliably identify diseases from fecal photographs, such as Newcastle disease, Coccidiosis, and Salmonella. Future developments in this field could include broadening the range of diseases identified, improving diagnostic precision through ensemble learning and fine-tuning techniques, incorporating cutting-edge technologies for decentralized model training, such as federated learning and edge computing, optimizing models for practical use on mobile devices, assessing long-term performance and scalability, and enhancing the interpretability and explainability of model decisions. Overall, the review of the literature highlights how deep learning has the potential to revolutionize the

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poultry industry. Overall, the review of the literature emphasizes how deep learning has the potential to completely transform the management of chicken diseases and points up directions for further study and advancement in this crucial field of agricultural technology.

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